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# Attractor dynamics of elite performance: the high bar longswing

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**ABSTRACT**

Combining biomechanics and motor control, the aim of this study was to investigate the limit cycle dynamics during the high bar longswing across the UK elite gymnastics pathway age groupings. Senior, junior and development gymnasts (N = 30) performed three sets of eight consecutive longswings on the high bar. The centre of mass motion was examined through Poincaré plots and recurrence quantification analysis exploring the limit cycle dynamics of the longswing. Close to one-dimensional limit cycles were displayed for the senior (correlation dimension (CD) = 1.17 ± .08), junior (CD = 1.26 ± .08) and development gymnasts (CD = 1.33 ± .14). Senior elite gymnasts displayed increased recurrence characteristics in addition to longer longswing duration ($p < .01$) and lower radial angular velocity of the mass centre ($p < .01$). All groups of gymnasts had highly recurrent and predictable limit cycle characteristics. The findings of this research support the postulation that the further practice, experience and individual development associated with the senior gymnasts contribute to the refinement of the longswing from a nonlinear dynamics perspective. These findings support the idea of functional task decomposition informing the understanding of skill and influencing coaches' decisions around skill development and physical preparation.

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**KEYWORDS**
Dynamical systems; motor control; correlation dimension; recurrence; gymnastics; longswing

## Introduction

Biological systems described by their attractor dynamics, with reference to recurrence and predictability, provide a framework to understand the fundamental characteristics of skilled performance. Since traditional biomechanics can quantify the biomechanical demands of individual skills, further understanding of skill development can be obtained by determining the attractor dynamics and investigating how movement control evolves in time through practice. Mathematical concepts, embedded within nonlinear dynamics, underpin the dynamical systems approach for understanding the emerging, self-organising processes of coordination (Haken et al., 1985; Kelso, 1995; Kugler & Turvey, 1987; Profeta & Turvey, 2018), and analysing sports performance (Beek et al.,

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1995; Irwin et al., 2019; Vicinanza et al., 2018). One challenge is to understand how coordination and control evolve in a complex, dynamical system to allow for the emergence of new and evermore functional patterns that satisfy the biomechanical and behavioural constraints (Newell, 1985; Waldrop, 1992).

Evidence suggests that most biological systems tend to settle into relatively few preferred coordination patterns, emerging as functional attractor states, whereby ordered behaviour is observed (Kauffmann, 1995). Kelso and Ding (1993) stated that within movement systems, attractors are generated through 'an infinite number of unstable periodic orbits' (p. 304), implying that even within the most stable systems; a certain level of variability is present to allow for flexibility. The time dependence of nonlinear measures can reveal properties of the dynamics that are not typically uncovered with traditional biomechanical analysis (Newell & Slifkin, 1998; Stergiou, 2004). These measures will allow coaches to decompose the task and better conceptually understand how the skill 'works' as highlighted by the model of Irwin et al. (2005).

The longswing has the inherent characteristics of a periodic attractor, specifically the closed-trajectory features of a limit cycle, whereby repeated rotations are maintained through energy input (Beek et al., 1995; Irwin et al., 2019; Vicinanza et al., 2018). The longswing is a task in which gymnasts rotate around the high bar from handstand to handstand (Hiley & Yeadon, 2003), where angular momentum dictates the successful skill (Figure 1). The longswing is recognised as an important skill in gymnastics that supports the development of more complex skills on the high bar (Hiley & Yeadon, 2003; Irwin & Kerwin, 2005, 2007a). Elite male gymnasts from around the age of 8 years are expected to have mastered the longswing and perform the skill with consistency and precision throughout their development, junior and senior career. However, from

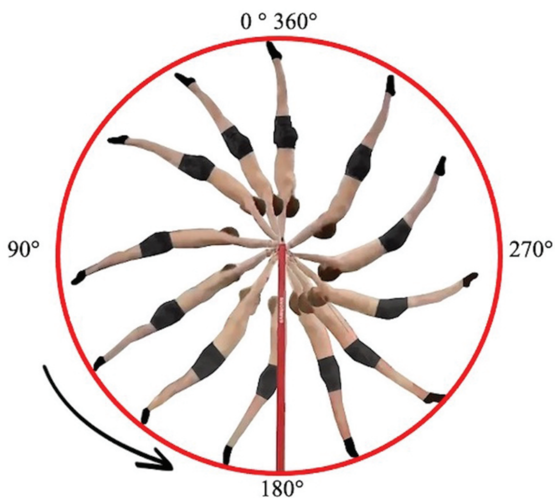


**Figure 1.** A gymnast performing a backward longswing on high bar. A circle angle of 0° represents the gymnast in handstand above the bar and directly under the bar at 180°. Quartile 1 = 1°-90°, quartile 2 = 91°-180°, quartile 3 = 181°-270° and quartile 4 = 271°-360°. Arrow denotes the direction of the longswing.

a dynamical systems perspective, how this complex system is controlled and organised throughout the evolution to becoming an elite gymnast has received limited study.

Gymnasts specialise in the sport at an early age, experiencing increased contact time with coaches, which can lead to higher levels of acute skill development (Feeley et al., 2016; Hartley, 1988; Root et al., 2019). Within the UK, performance-level gymnasts compete in age groups and are expected to continue along the development squad (up to 14 years) performance pathway through to junior (14–18 years) and senior squads (18 years and over) to compete at both national and international level. Gymnasts within the development, junior and senior groups all share an ability to successfully perform the general longswing (i.e., handstand to handstand) at their preferred pace without the need to perform a more complex skill. The gymnasts sharing an elite status, however, differ in age group classification (development, junior and senior). Although all gymnasts are biomechanically competent with the longswing skill, the nonlinear dynamics approach may reveal differences in the coordination, control and skill stages of learning (Newell, 1985) within and between these three groups. A reduced correlation dimension (CD) and increased recurrence quantification analysis (RQA) measures (e.g., determinism and length of diagonals) are more indicative of the skill stage of learning, with increased CD and reduced RQA measures suggestive of the coordination and/or control stages of learning. Vicinanza et al. (2018) compared an elite gymnast and non-elite gymnasts performing the longswing and highlighted higher levels of correlation dimension for the non-elite gymnasts compared to the elite gymnast, suggesting a coordination/control stage of learning compared to the skilled stage between the two athlete groups.

High bar routines performed by all elite age groups include multiple longswings (Readhead, 1997). Understanding the longswing skill has been approached from a number of scientific paradigms, including forward dynamics modelling (Hiley & Yeadon, 2003), biomechanical approaches (Arampatzis & Brüggemann, 2001; Irwin & Kerwin, 2005; Williams et al., 2012) and more recently from the nonlinear dynamics perspective (Vicinanza et al., 2018). Vicinanza et al. (2018) examined the limit cycle characteristics of the longswing, recognising the potential use of this nonlinear dynamics approach to understanding skill development. Building on the underlying biomechanical work and employing the nonlinear dynamics approach, this study employed a cross-sectional design with the three UK age groups of elite gymnasts (development, junior and senior). Understanding the limit cycle and its characteristics would allow insights into the constructs of movement control (Schöner & Kelso, 1988) complexity (Van Emmerik et al., 2016) and predictability (Kelso et al., 1981) of the longswing.

The aim of this study was to investigate the limit cycle dynamics during the high bar longswing across the UK elite gymnastics pathway age groupings (development, junior and senior). The purpose of this study was to use biomechanics and nonlinear dynamics concepts to provide a more accurate task decomposition, potentially allow for better conceptual understanding of skill, and potentially make training more effective. It was hypothesised that all groups would show similar qualitative properties of the limit cycle trajectory in terms of shape and size in phase space due to the basic nature of the task and the elite nature of a particular cohort. However, it was additionally hypothesised that senior gymnasts would show further dynamical refinement of quantitative RQA measures reflecting increased recurrence and predictability of the longswing dynamics compared to junior and development gymnasts.

## Methods

### Participants

Prior to the onset of the study, ethical approval was gained from the XXXX University Ethics committee. Thirty elite-level male artistic gymnasts gave voluntary informed consent to partake in the study. All gymnasts were performing at the highest possible level within their age category, competing at national and/or international competitions. Ten senior level (age: 20.4 ± 3.0 years, mass: 64.0 ± 6.5 kg, stature: 1.65 ± 0.07 m, gymnastics experience: 12.7 ± 2.9 years), 10 junior level (age: 15.0 ± 0.6 years, mass: 49.4 ± 7.6 kg, stature: 1.59 ± 0.08 m, gymnastics experience: 7.0 ± 1.2 years), and 10 development level gymnasts (age: 10.4 ± 1.0 years, mass: 33.2 ± 6.6 kg, stature: 1.27 ± 0.16 m, gymnastics experience: 4.5 ± 1.9 years) were recruited. A legal parent or guardian provided informed consent for participants under the age of 18 years. Each participant performed three sets each of a series of eight consecutive looped longswing. Participants were looped to the high bar to ensure safety and were familiar with performing the looped longswing within regular training.

### Data collection and processing

An automated 3D motion capture system (CODAmotion, Charnwood Dynamics Ltd, Leicester, UK) sampling at 100 Hz captured all kinematic data. Two CX1 scanners provided a field of view exceeding 2.5 m around the centre of the bar (Williams et al., 2012). Eight active CODA markers (three x XM-200 and five x XM-400) were attached to four-marker drive boxes and affixed to the gymnast and high bar. Markers were positioned unilaterally on the fifth metatarsophalangeal joint, lateral malleolus, lateral femoral condyle, greater trochanter, estimated centre of rotation of the glenohumeral joint, lateral epicondyle of the elbow and mid forearm, with an additional marker on the underside of the centre of the bar. All calculations were based on the relative movement of the gymnast and the bar.

Raw marker data from both the vertical and horizontal directions were determined from CODA output and all of the following examination was undertaken in R (http://www.r-project.org) using a modified code (Vicinanza et al., 2018). Density values were obtained from De Leva (1996). Based on the body segment inertia parameters, the principle of moments was used to calculate the centre of mass (CM) location of the performer. The angular orientation of the gymnast about the bar was defined by the circle angle ($\theta_c$). Circle angle was distinguished by the CM to bar vector with respect to the horizontal, where a $\theta_c$ of 0° and 360° defined the gymnast's CM as above the bar (in handstand). Moment of inertia and angular velocity of the CM of the gymnast about the bar are denoted as MoI and ωCM, respectively. Using an adapted version of Hof's (1996) gait method, MoI was normalised to a gymnast-specific inertia value (in handstand above the bar) and denoted as the percentage of a straight somersault position. Data were interpolated using a cubic spline to 1° increments of overall $\theta_c$ about the bar to allow for intra-trial comparisons. A fourth-order low-pass Butterworth filter was used to filter kinematic data with a cut-off frequency of 12 Hz obtained through a residual analysis (Winter, 2009).

## *Data analysis*

*Poincaré plots*: Poincaré plots (Kantz & Schreiber, 2004) were used to denote the CM trajectory in the phase space as an initial step to examine the presence of attractor dynamics (Vicinanza et al., 2018). Takens (1981) theorem states that the Takens' vector enables the reconstruction of an equivalent dynamical system to the original system that is produced by the observed time series. Embedding the time series in an n-dimensional space generates the set of Takens' vectors. The n-th Takens' vector is defined as:

$$\mathrm{T}[\mathrm{n}] = \backslash\mathrm{time.series}[\mathrm{n}], \mathrm{time.series}\,[\mathrm{n} + \mathrm{timeLag}], \ldots \mathrm{time.series}\,[\mathrm{n} + \mathrm{m} * \mathrm{timeLag}] \quad (1)$$

Takens' theorem reconstructed the longswing limit cycle through embedding the ωCM time series in a 3-dimensional space (Kennel et al., 1992). Time-delayed minimum mutual information (taking into account nonlinear correlations) and false nearest neighbours techniques were used to generate an appropriate time lag of 16 points (Fraser & Swinney, 1986) and embedding dimension of 3 (Kennel et al., 1992). Each Poincaré plot displayed the CM trajectory in the phase space for one trial (eight continuous longswing) for each gymnast.

*Correlation dimension (CD)*: CD is a measure of fractal dimension and is an approximation of the number of independent pairs of the state coordinates on the attractor (Stelter & Pfingsten, 1991), delivering further understanding into the effective number of dynamical degrees of freedom (DoF). CD was used to assess the dimensionality of the ωCM about the bar across eight consecutive longswing for each gymnast. CD quantifies the number of dimensions needed to capture the deterministic structure of the longswing. Grassberger and Procaccia (1983a, 1983b) algorithm was used to estimate CD. A mean average CD was taken for each participant across the 24 longswing within the three performed trials and subsequently averaged for each age group.

*Recurrence plots*: Through measures of recurrence point density and diagonal structures, RQA and Poincaré analysis were used to investigate the capability of the system to return to the same condition within a certain boundary, providing an insight into the reproducibility of the signal (Castanié, 2006; Van Emmerik et al., 2016; Zbilut & Webber, 1992). RQA allows for nonlinear data analysis of a dynamical system, quantifying the duration and number of recurrences presented within the generated state space (Marwan et al., 2007).

Recurrence plots displayed results for the ωCM time series for eight consecutive longswing performed by each gymnast within a single trial. Percentage determinism was determined with a radius r = 0.08, to calculate the quantity of recurrent points organised into diagonal line structures in the recurrence plots. The longest length of diagonals ($L_{max}$) and the mean length of diagonals ($L_{mean}$) were identified from each recurrence plot to indicate, within 8% of the maximum variability, the predictability of the longswing dynamics across each swing. $L_{max}$ and $L_{mean}$ values were divided by the sampling frequency to gain the time at which the longswing dynamics can be predicted across each swing.

## *Statistical analysis*

A one-way analysis of variance examined the effect of group seniority on each individual variable. A Bonferroni post hoc test was then used to examine where differences were found; the alpha level was set at $p \leq .05$. Hedges g calculations were used to generate between-group effect sizes ($g$) for all discrete variables where small effect = 0.2, medium effect = 0.5 and large effect = 0.8 (Cohen, 1977). Statistical tests were processed using the IBM SPSS Statistics 26 Software (IBM SPSS, Inc., Chicago, IL, USA).

## Results

### *Biomechanical measures*

Tables 1 and 2 show the biomechanical characteristics of the longswing with specific reference to longswing time, ωCM and MoI. Senior gymnasts displayed the highest individual longswing times and lowest ωCM for the whole swing and within each quartile in comparison to junior and development gymnasts. Significant differences were found for individual longswing time and ωCM between groups across the whole swing and each quartile ($p < .05$).

Post hoc analysis revealed significantly faster longswing times and lower ωCM values for development gymnasts in comparison to senior gymnasts across the whole swing and all four quartiles ($p < .001$). Development gymnasts had significantly faster longswing

**Table 1.** Mean (±SD) individual longswing (LS) time (s), angular velocity of the gymnast's mass centre about the bar (ωCM) (rad/s) and normalised total body moment of inertia (MoI) (% straight somersault (ss) position) for the whole swing and across each quartile of the swing for senior, junior and development gymnasts.

| Mean ± SD | Whole | Quartile 1 | Quartile 2 | Quartile 3 | Quartile 4 |
|---|---|---|---|---|---|
| *Senior* | | | | | |
| LS Time (s) | 1.77 ± 0.86 | 0.59 ± 0.21 | 0.35 ± 0.03 | 0.37 ± 0.02 | 0.56 ± 0.23 |
| ωCM (rad/s) | 3.55 ± 0.12 | 2.65 ± 0.24 | 4.47 ± 0.16 | 4.26 ± 0.19 | 2.82 ± 0.28 |
| MoI (%ss) | 90.89 ± 2.04 | 96.36 ± 3.25 | 89.55 ± 2.54 | 82.37 ± 3.52 | 92.15 ± 3.56 |
| *Junior* | | | | | |
| LS Time (s) | 1.64 ± 1.01 | 0.58 ± 0.26 | 0.33 ± 0.03* | 0.33 ± 0.02* | 0.54 ± 0.28 |
| ωCM (rad/s) | 3.82 ± 0.14 | 2.70 ± 0.13 | 4.83 ± 0.21* | 4.80 ± 0.36* | 2.93 ± 0.20 |
| MoI (%ss) | 94.07 ± 1.34 | 98.44 ± 0.58 | 94.07 ± 1.17 | 88.55 ± 8.70 | 93.31 ± 2.19 |
| *Development* | | | | | |
| LS Time (s) | 1.53 ± 0.66*^ | 0.52 ± 0.16*^ | 0.31 ± 0.02*^ | 0.32 ± 0.02* | 0.47 ± 0.17*^ |
| ωCM (rad/s) | 4.10 ± 0.17*^ | 3.02 ± 0.23*^ | 5.13 ± 0.18*^ | 4.91 ± 0.33* | 3.32 ± 0.26*^ |
| MoI (%ss) | 97.29 ± 2.15 | 98.05 ± 3.35 | 96.01 ± 1.15 | 93.57 ± 2.68 | 97.87 ± 2.42 |

*denotes significant difference to senior gymnasts ($p \leq .05$). ^ denotes significance difference to junior gymnasts ($p \leq .05$).

**Table 2.** Hedges' g effect sizes ($g$) for individual longswing (LS) time, gymnast mass centre angular velocity about the bar (ωCM) and moment of inertia (MoI) across senior (Snr), junior (Jnr) and development (Dev) gymnasts.

| Hedges *g* effect size | | Whole | Quartile 1 | Quartile 2 | Quartile 3 | Quartile 4 |
|---|---|---|---|---|---|---|
| LS Time (s) | Snr—Jnr | 0.13 | 0.05 | 0.88 | 1.92 | 0.08 |
| | Snr—Dev | 0.30 | 0.38 | 1.59 | 2.29 | 0.39 |
| | Jnr—Dev | 0.13 | 0.27 | 0.70 | 0.32 | 0.26 |
| ωCM (rad/s) | Snr—Jnr | 2.04 | 0.28 | 1.51 | 1.88 | 0.48 |
| | Snr—Dev | 3.70 | 1.59 | 2.96 | 2.45 | 1.88 |
| | Jnr—Dev | 1.78 | 1.71 | 1.56 | 0.32 | 1.69 |
| MoI (%ss) | Snr—Jnr | 0.15 | 0.05 | 0.13 | 0.53 | 0.22 |
| | Snr—Dev | 0.17 | 0.29 | 0.18 | 0.20 | 0.17 |
| | Jnr—Dev | 0.12 | 0.09 | 0.20 | 0.45 | 0.12 |

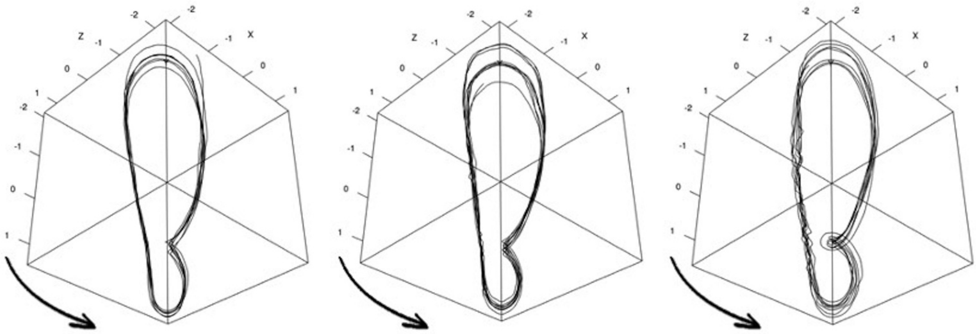


**Figure 2.** Poincaré plot representation of a senior (left), junior (centre) and development (right) gymnast across one full trial of eight longswings. Arrows denote the direction of the longswing.

times and higher ωCM values compared to junior gymnasts across the whole swing and within quartiles 1, 2 and 4 ($p < .001$) although no significant differences were found for quartile 3. Junior gymnasts showed significantly faster longswing times within quartiles 2 and 3 ($p < .001$, $g = 1.15$ and $p < .001$, $g = 1.71$, respectively) and significantly larger ωCM values within quartiles 2 and 3 ($p < .001$, $g = 0.88$ and $p < .001$, $g = 1.92$, respectively) in comparison to senior gymnasts. No significant differences were found between the groups for MoI ($p > 0.05$).

### *Phase space and correlation dimension*

Poincaré plots (Figure 2) denote the closed-loop limit cycle trajectories in phase space. Position divergence from a perfect elliptical shape can be clearly observed within the Poincaré plots for all gymnasts. The CD of the Poincaré plot trajectory is close to one-dimension for senior, junior and development gymnasts (1.17 ± .08, 1.26 ± .08 and 1.33 ± .14, respectively) (Table 3); however, significant differences were found for CD between groups ($F(2,87) = 19.215$, $p < .001$). Post hoc analysis revealed significantly lower CD for senior gymnasts in comparison to junior ($F(2,87) = 19.215$, $p < .001$, $g = 1.04$) and development gymnasts ($p < .001$, $g = 1.39$), with junior gymnasts exhibiting significantly lower CD when compared to development gymnasts ($p = .009$, $g = 0.67$).

**Table 3.** Mean ± standard deviation, Hedges' g effect size (*g*) and 95% confidence intervals (CI) for correlation dimension (CD), percentage determinism (DET) and mean ($L_{mean}$) and longest ($L_{max}$) length diagonals within recurrence plots across senior (Snr), junior (Jnr) and development (Dev) gymnasts.

| | CD | DET (%) | $L_{mean}$ (s) | $L_{max}$ (s) |
|---|---|---|---|---|
| Snr | 1.17 ± 0.08 | 99.41 ± 0.01 | 0.33 ± 0.13 | 2.03 ± 1.01 |
| Jnr | 1.26 ± 0.08 * | 99.42 ± 0.01 | 0.25 ± 0.08 * | 1.97 ± 0.88 |
| Dev | 1.33 ± 0.14 *^ | 99.41 ± 0.01 | 0.23 ± 0.09 * | 1.82 ± 0.40 |
| *g* [95% CI] | | | | |
| Snr—Jnr | 1.04 [0.11–1.98] | 0.00 [−0.87–0.88] | 0.10 [−0.78–0.98] | 0.70 [−0.27–1.60] |
| Snr—Dev | 1.39 [0.41–2.37] | 0.00 [−0.88–0.88] | 0.70 [−0.20–1.61] | 0.86 [−0.05–1.78] |
| Jnr—Dev | 0.67 [−0.23–1.57] | 0.00 [−0.88–0.87] | 0.21 [−0.67–1.09] | 0.25 [−0.63–1.13] |

*denotes significant difference to senior gymnasts ($p \le .05$). ^ denotes significance difference to junior gymnasts ($p \le .05$).

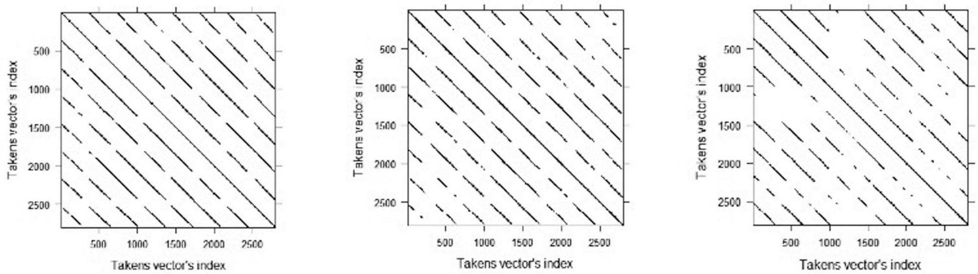


**Figure 3.** Recurrence plot representation of a senior (left), junior (centre) and development (right) gymnast across one full trial of eight longswings.

### *Recurrence analysis*

Recurrence provides a measure of the limit cycle reproducibility. Shorter lengths of diagonal lines within the recurrence plots displayed lower recurrence rates in phase space for development gymnasts compared to senior and junior gymnasts over eight longswing (Figure 3). Recurrent points formed distinct diagonals parallel to, but offset from, the main diagonal (line of origin), typical of a periodic deterministic structure. Percentage determinism was extremely high across all participants (Table 3).

$L_{max}$ and $L_{mean}$ (Table 3) were highest for senior gymnasts and lowest for development gymnasts. Significant differences were found for $L_{mean}$ between groups ($F(2,87) = 9.134$, $p < .001$) with post hoc analyses revealing significantly higher $L_{mean}$ for senior gymnasts in comparison to junior ($F(2,87) = 9.134$, $p = .004$, $g = 0.10$) and development gymnasts ($p < .001$, $g = 0.70$).

## Discussion and implications

Understanding the biomechanics and nonlinear dynamics of the longswing across elite age groupings provides more functional task decomposition and better conceptual understanding of skill and potentially informs training practices. All gymnast groups displayed similar qualitative properties of the limit cycle trajectory in terms of shape and size in phase space, satisfying the first research hypothesis. The second hypothesis was also accepted as senior gymnasts exhibited further dynamical refinement of quantitative RQA measures compared to junior and development gymnasts.

Gymnasts are trying to maintain rotation around the bar. In the downswing, the gymnast is making their body as long as possible to try to create a turning force down towards the ground alongside gravity, which builds angular momentum in quartile 1 and 2 of the longswing. Due to air resistance, friction of the bar and the bar not being completely elastic and gravity acting, the gymnasts must alter their MoI to maintain the high angular velocity, displayed in quartile 3 in particular (Table 1). In quartile 4, gymnasts begin to lengthen their bodies once more, increasing MoI and decreasing ωCM to reach the handstand position above the bar to start the next longswing.

Biomechanical descriptions of the longswing recognised that the senior gymnasts had lower radial angular velocity of the CM and subsequently a longer duration of the skill. Other factors such as a more refined control of the skill (Vicinanza et al., 2018), more efficient swing technique (Yeadon & Hiley, 2000) and/or the notion of satisficing (Simon, 1956) could contribute to these differences. Employing nonlinear dynamics approaches will allow us to explore this further.

## Skill level and structure of longswing dynamics

The senior gymnasts had increased experience with longswing compared to the junior and development gymnasts due to number of practice hours. The most stable dynamics and lowest dynamical DoF were seen for the longswing of senior gymnasts, demonstrated by higher recurrence and lower CD, a finding that may demonstrate a task-specific relationship between stability and practice. Additionally, factors such as chronological age, skill level, practice and experience may also play a role in this finding. The identification of more stable dynamics and reduced DoF associated with practice and skill adds evidence to a long-debated area of motor control (Chow et al., 2008; Lee et al., 2016; Vereijken et al., 1992).

The longswing is an important skill for all gymnasts and a large part of their training, which may explain why only small differences were observed in the dynamical variables between groups. Nevertheless, since all gymnasts can fulfil the biomechanical task demands, it is projected that the increased stability and refinement within the longswing dynamics for senior gymnasts are a practice effect due to the efficiency and repeatability of the movement action (Ericsson et al., 1993).

The gymnasts in this study had varying levels of experience of performing this skill on high bars. The senior elite gymnasts would have, generally, learnt this skill by 8 years old and as such have been practicing and refining this skill for an average of 13 years. In contrast, the junior and development gymnasts have been practicing this skill for approx. 7 and 4 years, respectively. These practice durations and refinement periods would have played an important role in the emergence of the dynamics of the longswing. Senior gymnasts' refinement of the longswing has been driven by the need to meet the demands of more complex manoeuvres such release-regrasp skills. The idea of a refined longswing concurs with the observations that the dynamics are more predictable and displayed the strongest limit cycle attractors. Contrastingly, the development gymnasts are relatively early in their gymnastics careers and have been exposed to less training/practice time and do not possess the refined dynamics of their senior counterparts.

## Limit cycle and trajectory dynamics

The clear position divergence (corners or changes in direction) from a perfect elliptical shape observed in Figure 2 are associated with an increased level of energy being injected into the system. The position of these divergences in the phase space occurs at the points of the functional phase; the location of the energy input to maintain the repeated longswing (Irwin & Kerwin, 2007b), which is consistent across age groups of gymnasts. The low CD (range: 1.05–1.55) presented an attractor close to a one-dimensional limit cycle for all gymnast groups (Table 3). The lower CD of the limit cycle suggests decreased movement complexity (Decoster & Mitchell, 1991; Nayak et al., 2018) and infers that these gymnasts have reached the skill optimisation stage (Bernstein, 1967; Newell, 1985) further supported by the use of kinetics, which was highlighted by Bernstein (1967) to occur when the controller learns to use the force. The lower CD and reduction in dynamical DoF may be a result of the highly constrained task instructions and/or practice required for successful longswing performance.

The lower limit cycle CD and high determinism values shown for the senior gymnasts in this research suggest a highly stable, efficient and predictive movement trajectory. All gymnasts exhibited high determinism, indicating high signal reproducibility with few reactive adjustments (Zbilut & Webber, 1992), typical of consistent longswing performance. However, it is important to recognise the notion of functional variability required for flexible movement behaviour (Hiley & Yeadon, 2016; Stergiou et al., 2006); therefore, the perfect CD and determinism of 1, denoting perfect cyclical movement, is near impossible and likely undesirable even for high-performance athletes. As previously mentioned, this can be linked to the skill optimisation stage of learning (Newell, 1985).

## Intermittent control of the longswing

Recurrence plots (Figure 3) offer a method to visualise the periodic nature of the trajectory and the determinism of the longswing dynamics (Eckmann et al., 1987; Marwan et al., 2007). Shorter length diagonals were observed for the development gymnasts, which correspond to less predictable longswing dynamics and an increased intermittency of control. A higher frequency of feedback at different temporal intervals may be required by development gymnasts to correct deviations from the movement trajectory and continue swinging.

Findings from the Poincaré plots support the observations of Hiley et al. (2013) who indicated that elite gymnasts may be using more feedback control in the less mechanically important areas of the skill, in our case, quartiles 1 and 4 of the longswing. The development gymnasts may be using this in a larger portion of these quartiles of the longswing to make necessary corrections in comparison to the other groups to ensure that the lower portion of the longswing can be completed effectively. This could contribute to the more intermittent nature of the recurrence plots and the variation in limit cycle trajectory observed within the Poincaré, particularly for development gymnasts in quartile 1 and 4 of the longswing. The higher $L_{max}$ and $L_{mean}$ values for senior and junior gymnasts may be reflective of the increased practice opportunities (Ericsson et al., 1993) and a more automatic longswing technique, with less feedback required, generating a more deterministic limit cycle attractor. However, it is important to note that, in this instance, the feedback approach cannot be separated from other central contributions for intermittency (Gawthrop et al., 2011).

The increased $L_{max}$ and $L_{mean}$ values for the senior gymnasts, paired with the CD and recurrence findings evidence a reduction in complexity, increase in determinism and stability as gymnasts move further towards skill optimisation (Newell, 1985). The findings of this research support the notion that further practice, experience and individual development associated with the senior gymnasts seem to continue to refine the characteristics of the longswing. The application of these findings and the advantages of this approach can be set against the context of developing a conceptual mindset of the skill based on the movement patterns and body positions for successful performance (Gould et al., 1990; Irwin et al., 2005). Understanding the nonlinear dynamics components provides a way of holistically viewing the interaction of the more traditional biomechanics and the emergent properties and mechanisms that control the skill. Understanding these factors will allow coaches to decompose the task more effectively and develop a task- and age-specific mindset of the longswing, which could ultimately lead to identifying more effective physical preparation, rehabilitation and skill development pathways. This is something we aim to do in the future, building on the work of Irwin and Kerwin (2005, 2007a), Williams et al. (2012), Williams et al. (2015), and Busquets et al. (2016).

## Conclusion

The use of nonlinear dynamics provides a relevant scientific framework for understanding and explaining the control of the longswing. The increase in the deterministic nature of the cyclic movement, reduction in dimensionality and increased RQA measures of the senior elite gymnasts are indicative of a more skilled, more practiced group. The findings provide novel insights into movement control across three age groups of elite gymnasts and point to an evolving continuous refinement of the general longswing. From a coaching perspective, it is important to consider these changes in the gymnast's technique-training as they develop.

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